Application of CNN-BiLSTM transient electromagnetic inversion in the detection of coal seam gob

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SUMMARY

The traditional inversion method of transient electromagnetic is easy to fall into local optimal when dealing with non-uniform geoelectric structure, and it is difficult to meet the practical exploration requirement. In this paper, an inversion method based on convolutional bidirectional long short time memory neural network (CNN-BiLSTM) is introduced, which is applied to the precise inversion of fixed source large loop transient electromagnetic. This network structure has strong ability of extracting spatial features and understanding sequence data, which solves the problem of slow computation efficiency and insufficient accuracy of traditional inversion. Using the apparent resistivity of the three-layer model as the sample input and the real model as the sample target, the network is trained, and batch normalization and dropout techniques are used to accelerate the convergence of the network. Through numerical simulation experiments, the inversion efficiency of this method is much better than that of the traditional method, and it also has excellent inversion accuracy and geoelectric stratification ability. The CNN-BiLSTM inversion is applied to the measured coal seam gob detection, and the inversion effect is good, and it is consistent with the drilling verification results. This work provides a new and efficient inversion method for the transient electromagnetic exploration field, and has potential application prospects in other fields.

Keywords: Transient electromagnetic method; Inversion; Deep learning network; CNN-BiLSTM

INTRODUCTION

Traditional transient electromagnetic methods (TEM) have low accuracy in detecting underground targets, and the decay voltage and the apparent resistivity value are generally used as interpretation parameters. Later, it was proposed to improve the resolution by inversion, which indeed enhanced the resolution and accuracy of detection, and promoted the development of TEM. However, the traditional inversion of TEM is inefficient and is difficult to deal with complex geoelectric structure. Due to the highly nonlinear characteristics of transient electromagnetic inversion, the commonly used linear inversion methods such as least squares are often highly dependent on the initial model and easily fall into the local optimal solution, leading to problems such as unclear reflection of the abnormal body boundary and slow calculation speed.

The researchers then improved the inversion algorithm. Occam inversion were proposed to conduct smooth inversion of fixed layer thickness(Constable et al., Chen et al., Zhang et al.), which improved the inversion speed and resolution, but was still limited by the influence of local minima. Some researchers have used particle swarm optimization algorithm (Cheng et al., 2014) and simulated annealing algorithm (Yin et al., 2007; Beaty et al., 2002), genetic algorithm (Shibutani et al.], 2013), Bayesian algorithm (Yin et al., 2014), etc., to achieve the purpose of finding the global optimal solution, have improved the inversion accuracy to some extent.

Some researchers have adopted neural network apparent resistivity imaging to improve computing efficiency, (Qin et al., 2019; Feng Bing et al., 2020; Wu et al., 2021; You et al., 2023), but the inversion accuracy was not improved. In recent years, due to the rapid development of deep neural networks, many possibilities have been provided for work in various fields, and the application prospect in geophysical exploration is promising. Wu et al. applied convolutional neural networks in airborne transient electromagnetic inversion, proving that they have higher adaptability and accuracy than the traditional inversion of Gauss-Newton algorithm. Davood applied convolutional neural networks to electromagnetic induction inversion. LSTM short-duration memory neural network can better analyze timing information, and some scholars have applied it to transient electromagnetic noise processing, and achieved good results (Wu et al., 2021). Subsequently, LSTM neural networks were used for real-time ground transient electromagnetic inversion (Fan Tao et al., 2022), and the inversion speed and effect were better than traditional inversion. Not only that, LSTM neural networks are also suitable for airborne transient electromagnetic instantaneous inversion systems, greatly speeding up and being applied in practice (Wu et al., 2022).

Compared with the traditional LSTM model, CNN-LSTM model has more flexibility and expression ability due to the addition of CNN to extract spatial features (Chiu, 2015). Some researchers have also applied CNN-LSTM model to geophysical logging (Shan et al., 2021) and rapid imaging of TEM (Xian et al., By 2022). However, the BiLSTM model is better than LSTM in processing time series data (Siami-Namini, 2019), so CNN-BiLSTM will have more advanced performance. Some scholars have also done some work to improve TEM inversion technology by using CNN-BiLSTM deep neural network, such as CNN-BiLSTM real-time inversion (Gu Yao et al., 2023).

In this paper, an advanced convolutional bidirectional long short-time neural network (CNN-BiLSTM) is introduced for TEM one-dimensional (1D) inversion. CNN-BiLSTM combines a convolutional layer and a BiLSTM layer for processing data with temporal and spatial relationships. A large number of sample data are trained and learned on the network, and finally the inversion network model is obtained. The result can be predicted by inputting the data into the network model.

METHODS

Convolutional neural network (CNN) convolves the input data by convolutional checking, and passes the convolved results to the next layer for processing. It uses a convolutional layer to identify features and downsamples these features through a pooling layer, thereby reducing the number of parameters and improving computational efficiency. In the field of deep learning, CNN is a very popular model. When CNN is used for problems in the field of geophysics, it can extract effective information from transient electromagnetic signals through feature mapping, which has certain advantages in the inversion of formation dielectric parameters.

alignment and single line spacing with the following exceptions:

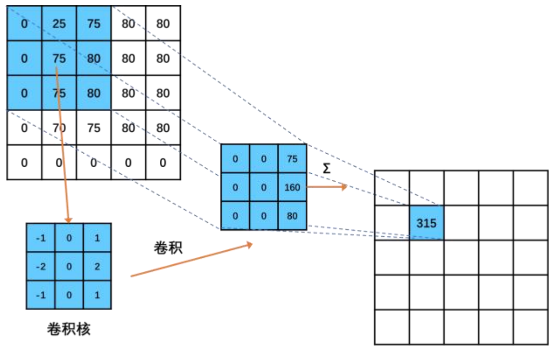


Fig 1 Convolutional layer operation diagram

LSTM network is characterized by a CELL STATU with memory, which is connected with the forgetting gate, update gate and output gate (see Figure 1-2). In the figure, t, x and h represent time input data and prediction result and cell state. Sigmoid and tanh are activation functions, mult and add are operational operations. The cell state itself contains the memory of the previous time, and the cell state is selectively retained or forgotten through the forgetting gate in order to better capture the correlation in the time series; Control the inflow of new input data through the input gate, filter the valid information and update the unit status; Information is controlled to flow out or continue to be passed back through the output gate by weighting the information in the cell state with the current input. This special CELL STATU with "memory" allows the LSTM network to better understand time series data and extract the temporal characteristics of long-term dependencies.

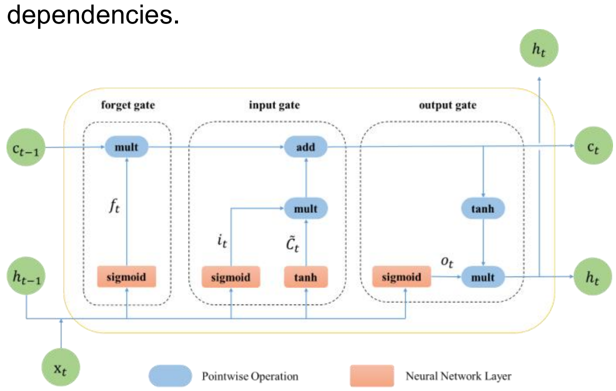


Fig 2 Internal structure diagram of LSTM neural network unit

The forward response of TEM was first calculated and then by using the fast algorithm of global apparent resistivity of neural network (You et al., 2023), so as to obtain the apparent resistivity data. The apparent resistivity is taken as the input training sample set, and the resistivity of the real model is taken as the target sample set. We uses the formula of the smoke ring theory (Nabighian, 1979) to calculate the depth as the training sample.

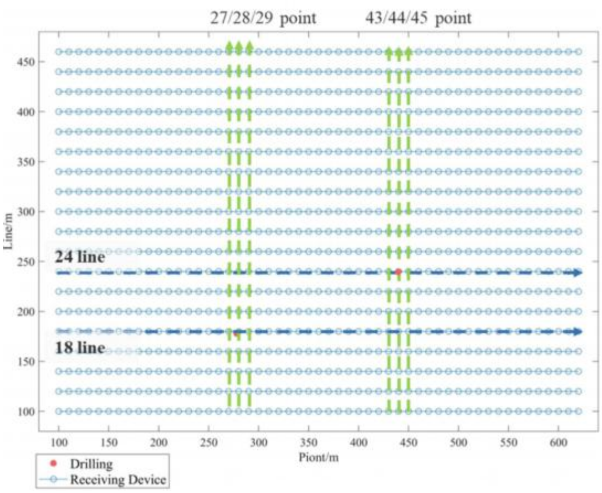
Thus, the true resistivity formation model is defined. In order to ensure the stability and effect of neural network training and learning, the idea of fixed corresponding layer thickness of Occam is used for reference. At the same time, in order to improve the stability of data for network training, it is necessary to normalize training samples and target samples. The training model is a three-layer model, covering two-layer model and half-space model. The training samples are obtained by batch forward modeling with full permutation and combination. The parameters of the training sample set are shown in Table 1.

Table 1 Parameters of training sample

Parameters		Parameters	
Resistivity range	10Ωm：1000Ωm	Resistivity number	19
Time windows	1e-4s：1.316e-2s	Time channels	100
Thick range	25：300m	Detection depth	600m
Models number	372,096 group	Loop side length	200m×200m
Input parameter	Apparent resistivity	Target parameter	Real model

RESULTS

The inversion method is applied to the detection of coal seam gob in Inner Mongolia. A large fixed source loop device with a transmission loop of 120m × 200m was adopted to observe within a uniform field range of 40m×120m in the middle of the transmission frame with a transmission frequency of 25Hz. The layout of the survey line and the drilling position are shown in FIG. 3-2.



. Fig 3 Drilling position and survey line layout

The horizontal coordinate represents the survey line (line distance is 20m) and the vertical coordinate represents the measurement point (point distance is 10m).

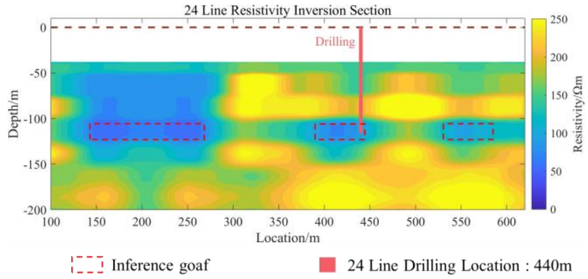


Fig 4 24-line inverse resistivity profile

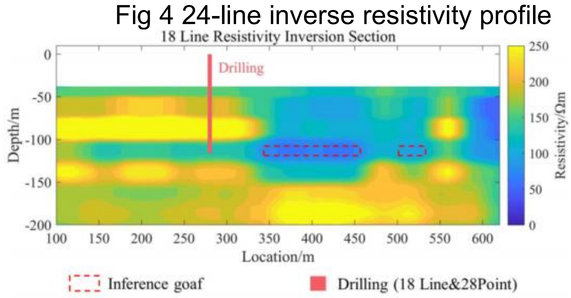


Fig 5 18-line inverse resistivity profile

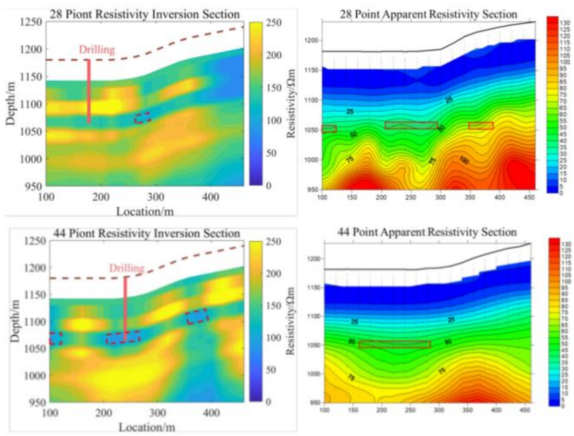


Fig 6 Inversion resistivity and apparent resistivity profiles at the same measurement points 44 and 28

From the inversion profile, it can be clearly seen that the stratification trend is low-high-low-high layer, and the coal seam is high resistivity. According to the geological data, the coal seam is concentrated in the depth of 50m-100m, and the shallow layer of sand and mudstone is formed in the depth of 50m. The depth of 100m to 125m has obvious low resistance layer, which is speculated to be the horizontal position of the mined-out area of coal seam. The Location = [150m-250m]/[450m to 500m]/[530-580m] three locations have obvious low resistance, which is presumed to be the mined-out area. After drilling verification, 112.5m-114m can not take out the core, serious water leakage; The drilling suddenly dropped at 114m to 116.3m, and water could not return there, so it was concluded that the depth of 114m-116.3m was a goaf, which was consistent with the inversion results.

According to the geological conditions, the abnormal delineation of the gob can only be roughly delineated. After inversion, the abnormal position of the obvious layer structure on the whole section is also more obvious, which also conforms to the drilling verification and the rough drilling layer system.

DICUSSION

First,CNN-BILSTM inversion can be used to processing the field data of coal mine goaf and good results can be obtained. This area belongs to the Ordos Basin, the geological structure is relatively simple, basically stratified distribution, which is also in line with the deep learning network sample in this paper, based on the one-dimensional model of stratified formation. If the actual stratum is a complete three-dimensional stratum, whether the inversion method proposed in this paper can get the ideal effect needs to be further demonstrated. If the prior information of the actual stratum can be added to the sample training in advance, the inversion effect will be better. The next step will be to combine deep learning and prior constraints to further optimize inversion methods based on deep learning. Second, Compared with the apparent resistivity, the inversion results are more precise. Although the inversion is non-unique, in order to carry out fine detection, various optimization and constrained inversion must be carried out on the basis of the apparent resistivity, and only in this way can close to the real geo-electric cross-section be achieved. In addition, The actual loop size often changes greatly, and some of them are even rectangular loop, while the sample training set often adopts square loop, and the transmitting area is inconsistent with the actual transmitting loop area. The actual loop size can be corrected to the loop size used by the sample set through the calibration of the loop size, and then the inversion is carried out, which has certain feasibility and can save a lot of sample training time.

CONCLUSION

In this paper, CNN-BiLSTM deep neural network is studied, and a new inversion algorithm is realized by combining it with transient electromagnetic one-dimensional inversion algorithm. The inversion speed is extremely fast, only 2.48 seconds to invert 100 measurement points, greatly improving work efficiency.Finally, the inversion method can be applied to the measured data of the gob in coal field, and the inversion results not only have better resolution and layer structure than the apparent resistivity, but also accord with the field drilling verification. This method provides a new and efficient solution for shallow surface transient electromagnetic exploration, and provides effective technical support and ideas for other application fields

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